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NEURAL NETWORKS, ARIMA AND ARIMAX MODELS FOR FORECASTING INDONESIAN INFLATION

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Abstract

The objective of this study is to apply Neural Networks (NN) model for forecasting Indonesian inflation and to compare a result with ARIMA and ARIMAX models. The Feedforward Neural Networks (FFNN) model is the most popular form of artificial Neural Networks model used for forecasting, particularly in economics and finance. This study focuses on the model building of FFNN as time series model and use inflation rates in Indonesia. A comparison is drawn between FFNN model, and the best existing models are based on traditional econometrics time series approach, namely ARIMA and ARIMAX models. The best models are selected based on forecasting ability by using the MSE and RMSE, particularly on the dynamic forecast. The result shows that FFNN models outperform the traditional econometric time series model.

***Keywords*: Feedforward Neural Networks, inflation, dynamic forecasting**

Introduction

During the last few years, the use of the Neural Networks (NN) in economic literatures, particularly in the areas of financial statistics and exchange rates has grown and received a great deal of attention. Some publications about it can be found in Refenes and White (1998), Kaashoek and Van Dijk (2001, 2002), Hamid and Iqbal (2004), and Versace *et al.* (2004).

Feedforward Neural Networks (FFNN) model is the most popular form of NN models used for forecasting, particularly in economics and finance. FFNN is a class of flexible nonlinear models that can discover patterns adaptively from the data. The use of the NN model in applied work is generally motivated by a mathematical result stating that under mild regularity conditions, a relatively simple NN model is capable of approximating any Borel-measureable function to any given degree of accuracy (see e.g. Cybenko (1989), Funahashi (1989), Hornik *et al.* (1989, 1990), and White (1990)).

The investigation of nonlinearities in time series data is important to macro-economic theory as well as forecasting, as illustrated, in seminal work by Brock and Hommes (1997), or Barnett *et al.* (2003). Recently, many studies have applied NN models to macroeconomic time series, particularly on the modeling and forecasting inflation. Several studies about inflation forecasting by using NN can be found in Swanson and White (1997), Moshiri and Cameron (1997), Stock and Watson (1998, 1999), Chen *et al.* (2001), Kabundi *et al.* (2003), and McNelis *et al.* (2004).

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This paper discusses and investigates the usefulness of FFNN for forecasting inflation in Indonesia. Two main issues that are suspected influencing inflation are also studied, i.e. the effect of increasing fuel price (also known as BBM) and the effect of Islamic Calendar (price tend to increase during Ramadhan and the Eids holiday). Finally, a comparison is drawn between FFNN model and the best existing models based on traditional econometrics time series approach.

Conceptual Framework

Inflation Forecasting

The investigation about forecasting inflation in a specific country has received a great attention for many macroeconomics researchers. For most central banks, one of monetary policy objectives is inflation. Given typical time lags, monetary policy needs to take into consideration with future inflation. Current inflation levels, which are themselves the result of past policies, may provide only vague information. Inflation forecasts that link future inflation to current developments can bridge this gap. This paper attempts to develop an inflation forecasting model for Indonesia that could serve as an input for policy setting for the Bank Indonesia (BI).

Moshiri and Cameron (1997) did a comparison study between NN and econometrics models for forecasting inflation in Canada. Stock and Watson (1999) and Chen *et al.* (2001) have studied NN for forecasting inflation in USA. Kabundi *et al.* (2003) discussed and compared between NN and econometrics models for forecasting inflation in South Africa. McNelis and McAdam (2004) have also studied about forecasting inflation in USA, Japan and some European countries by using "*Thick Model*" and NN.

In Indonesia, inflation modeling has been studied by Arief (1995) and Anglingkusumo (2005). Arief (1995) used econometrics approach by implementing three models; Meiselman model, Anderson-Karnosky model, and Causal model developed by Hsiao. Anglingkusumo (2005) implemented P-star model for monetary inflation analysis.

1. Econometrics Time Series Approach

Modeling and forecasting inflation by using econometrics time series approach is usually used by many researchers in past decades especially compare with NN model. In this section, we will give a brief review of some forecasting models from econometrics time series approach particularly ARIMA, Intervention Analysis and Calendar Variation Model.

a. ARIMA Model

The ARIMA model belongs to a family of flexible linear time series models that can be used to model many different types of seasonal as well as nonseasonal time series. The seasonal ARIMA model can be expressed as: (see e.g. Box *et al.* (1994) and Wei (1990))

$$\phi_p(B)\Phi_P(B^S)(1-B)^d(1-B^S)^D y_t = \theta_q(B)\Theta_Q(B^S)\varepsilon_t \,, \tag{1}$$

where S is the seasonal length, B is the back shift operator and ε_t is a sequence of white noises with zero mean and constant variance.

b. Intervention Analysis Model

Intervention analysis model is a time series method which is usually used to explain the effect of external and internal factors to the time series data. Some papers about the application of intervention analysis model can be found in Box and Tiao (1975), Bhattacharya and Layton (1979), Montgomery and Weatherby (1980), Enders *et al.* (1990), Leonard (2001), Suhartono and Hariroh (2003), Suhartono and Putra (2005).

The general class of intervention analysis models can be written as: (see e.g. Box *et al.* (1994) and Wei (1990))

$$Y_t = \frac{\omega_s(B)}{\delta_r(B)} B^b I_t + \frac{\theta_q(B)\Theta_Q(B^s)}{\phi_p(B)\Phi_P(B^s)} a_t \tag{2}$$

where b is the time delay for the intervention effect and I_t is intervention variable.

c. Calendar Variation Model

Calendar variation effects model was originally given by Bell and Hillmer (1983). Suhartono and Sampurno (2002) studied the effect of Eids holiday (as Islamic calendar effects) to the increasing number of train and plane passengers at Jakarta-Surabaya route by using calendar variation model. This approach was also used by Bokil and Schimmelpfennig (2005) for forecasting inflation in Pakistan. In general, the calendar variation model can be written as (see Cryer (1986))

$$Y_t = \alpha_1 C_t + \frac{\theta_q(B)\Theta_Q(B^s)}{\phi_p(B)\Phi_P(B^s)} a_t \tag{3}$$

where α_1 is the effect magnitude of calendar variation variable and C_t is calendar variation variable.

2. Feedforward Neural Network

Neural Networks (NN) are a class of flexible nonlinear models that can discover patterns adaptively from the data. Theoretically, it has been shown that given an appropriate number of nonlinear processing units, we can learn from experience and estimate any complex functional relationship with high accuracy. Empirically, numerous successful applications have established their role for pattern recognition and time series forecasting.

Feedforward Neural Networks (FFNN) is the most popular NN models for time series forecasting applications. Figure 1 shows a typical three-layer FFNN used for forecasting purposes. The input nodes are the previous lagged observations, while the output provides the forecast for the future values. Hidden nodes with appropriate nonlinear transfer functions are used to process the information received by the input nodes.

The model of FFNN in figure 1 can be written as

$$y_t = \beta_0 + \sum_{j=1}^{q} \beta_j f\left(\sum_{i=1}^{p} \gamma_{ij} y_{t-i} + \gamma_{oj} \right) + \varepsilon_t , \qquad (4)$$

where p is the number of input nodes, q is the number of hidden nodes, f is a sigmoid transfer function such as the logistic:

$$f(x) = \frac{1}{1+e^{-x}} , \qquad (5)$$

$\{\beta_j, j = 0,1,\Lambda ,q\}$ is a vector of weights from the hidden to output nodes and $\{\gamma_{ij}, i = 0,1,\Lambda ,p; j = 1,2,\Lambda ,q\}$ are weights from the input to hidden nodes. Note that equation (4) indicates a linear transfer function is employed in the output node.

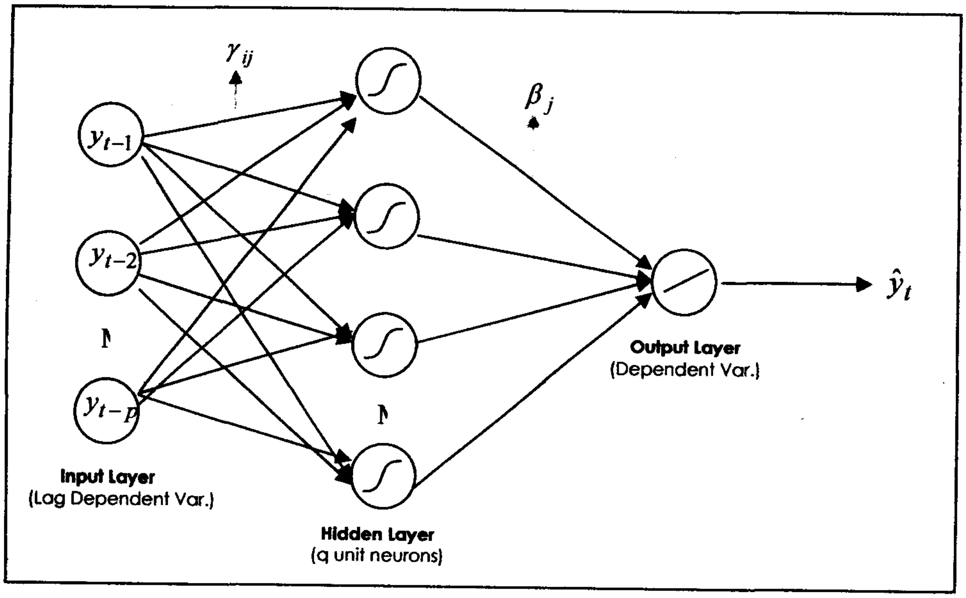

Figure 1. Architecture of Neural Network Model with Single Hidden Layer

Functionally, the FFNN expressed in equation (4) is equivalent to a nonlinear AR model. This simple structure of the network model has been shown to be capable of approximating arbitrary function (see e.g. Cybenko (1989), Funahashi (1989), Hornik *et al.* (1989, 1990), and White (1990)). However, few practical guidelines exist for building a FFNN for a time series, particularly the specification of FFNN architecture in terms of the number of input and hidden nodes is not an easy task.

Research Methodology

The purpose of this research is to provide empirical evidence on the comparative study between FFNN and traditional econometrics time series model for forecasting inflation in Indonesia. The major research questions we investigate are:

(i). Does FFNN have a better result on the accuracy for forecasting inflation in Indonesia than traditional econometrics time series model?

(ii). How to build the best FFNN model for forecasting inflation in Indonesia?

1. Data

The Indonesian inflation data that were used in this empirical study contain 76 month observations, started from January 1999 and ended in April 2005. The first 72 data observations are used for model selection and parameter estimation (training data in term of NN model) and the last 4 points are reserved as the test for forecasting evaluation and comparison (data testing). Figure 2 plots representative time series of this data. It is clear that the series has a stationary condition with little seasonal variations.

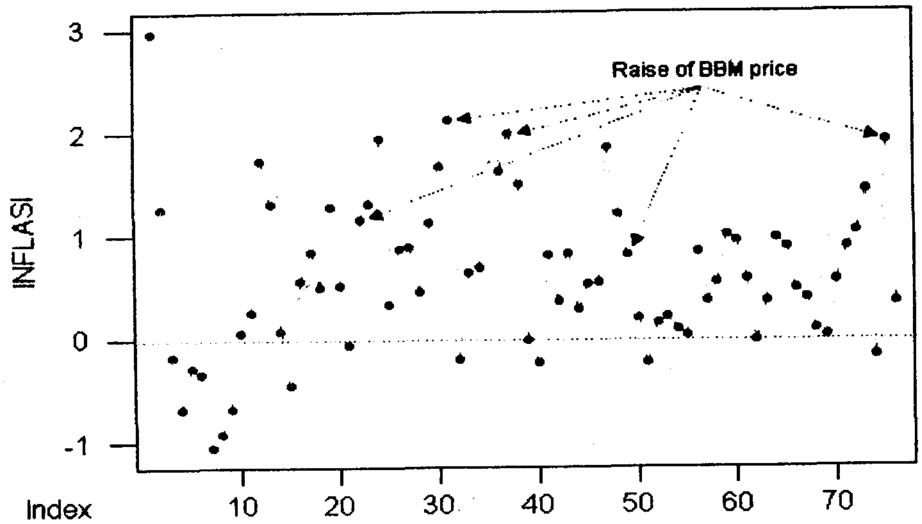

Figure 2. Time Series Plot of the Indonesian Inflation, started from January 1999 to April 2005

2. Research Design

In this research, four type models for forecasting inflation in Indonesia are applied and compared by implementing statistical package MINITAB and SAS for econometrics time series models and using S-Plus and MATLAB for FFNN models. Those models are ARIMA, Combination between Intervention and Variation Calendar Models, FFNN with input as ARIMA and FFNN with input as Combination Intervention and Calendar Variation Models.

To determine the best model, an experiment is conducted with the basic cross validation method. The available training data is used to estimate the parameters (weights) for any specific model. The testing set is the used to select the best model among all models considered. In this study, the number of hidden nodes for FFNN model varies from 1 to 6 with an increment of 1.

The FFNN model used in this empirical study is the standard FFNN with single-hidden-layer shown in Figure 1. The initial value is set to random with replications in each model to increase the chance of getting the global minimum. We did not use the standard data preprocessing in NN by transform data to [-1,1] and N(0,1) scale, because data inflation varies around 0. The performance of in-sample fit and out-sample forecast is judged by the commonly used error measures. They are the mean squared error (MSE) and the root mean square error (RMSE).

Empirical Results

In this section the empirical results for ARIMA, Combination Intervention and Variation Calendar (for simplicity we write ARIMAX) and FFNN models are presented and discussed.

1. Results of ARIMA Model

The identification step shows that the autocorrelation function (ACF) cuts off after lag 1 and significant at lag 11 and 12, while the partial autocorrelation function (PACF) also cuts off after lag 1 and significant at lag 10, 11 and 13. This suggests that seasonal ARIMA model should be used for the data. We estimate eight ARIMA models with seasonal length 11 and 12.

The results of forecast comparison by using MSE and RMSE criteria show that ARIMA$(1,0,0)(1,0,0)^{11}$ is the best model for out-sample forecast (data testing), while ARIMA$(0,0,1)(0,0,1)^{12}$ is the best model for in-sample forecast (training data), as shown in table 1. From this table, we can also observe that out-sample forecast of ARIMA models yield greater errors than in-sample forecast.

Table 1.
The Results of ARIMA Models, both in Training and Data Testing

Model	MSE		RMSE	
	Training data	Data testing	Training data	Data testing
▪ ARIMA(1,0,0)(1,0,0)^{11}	0.3576	0.682648	0.597997	0.826225
▪ ARIMA(0,0,1)(0,0,1)^{12}	0.2624	0.827925	0.512250	0.909904

2. Results of ARIMAX Model

Table 2 shows the results of three ARIMAX models that satisfy adequate model by testing parameter model and diagnostic check of residual model. From Table 2, we can conclude that intervention variable and Islamic calendar significantly influence the increasing of forecast accuracy, particularly in out-sample forecast.

Table 2.
The results of ARIMAX Models, both in Training and Data Testing

Model	MSE		RMSE	
	Training data	Testing data	Training data	Testing data
▪ Model 1	0.28626167	0.289602	0.535034	0.538147
▪ Model 2	0.29634263	0.240724	0.544374	0.490636
▪ Model 3	0.29359180	0.319303	0.541841	0.565069

These three models contain the effect of increasing BBM price and Islamic calendar to inflation data plus ARIMA model for the errors, i.e. ARIMA(0,0,[1,12]), ARIMA(0,0,1)(0,0,1)^{12} and ARIMA(1,0,0)(0,0,1)^{12} for model 1, 2 and 3 respectively. For example, model 1 can be formulated as

$$y_t = 0.4506 + 0.88556 I_t + 0.85634 C_t + (1 + 0.5111B + 0.2976B^{12}) a_t \quad (6)$$

where I_t is intervention variable (increasing of BBM price), C_t is Islamic calendar variable and B is backshift operator. This model shows that increasing the price of BBM and the Islamic Calendar (Ramadhan and Eids holiday) raised the inflation effect in Indonesia.

3. Results of FFNN Model

In this paper, building process for FFNN model particularly determination of inputs are based on the inputs of ARIMA and ARIMAX models. Table 3 summarizes the results of FFNN forecasting with input lags based on ARIMA and ARIMAX models.

The results show that the more complex of FFNN architecture (it means the more number of unit nodes in hidden layer) always yields better result in training data, but the opposite result happened in data testing. Moreover, FFNN models with input lags based on ARIMAX model give better forecast than ARIMA model. It can be clearly seen from the reduction of MSE and RMSE particularly in data testing.

Table 3.
The Results of FFNN Models, both in Training and Data testing

Model	Input lags	Number of neurons	Training data		Data testing	
			MSE	RMSE	MSE	RMSE
▪ FFNN with input lags based on ARIMA	1,12	1	0.3105369	0.557258	0.7257537	0.85191
		2	0.3031623	0.550602	0.7064180	0.84049
		3	0.2854341	0.534260	0.7579172	0.87058
		4	0.2057219	0.453566	1.0984050	1.04805
	1,11,12	1	0.2069178	0.454882	0.8657498	0.93046
		2	0.1891711	0.434938	0.8337273	0.91309
		3	0.1736372	0.416698	0.4711709	0.68642
		4	0.1418450	0.376623	0.8205497	0.90584
		5	0.1235492	0.351496	1.3148560	1.14667
▪ FFNN with input lags based on ARIMAX	1,12 I_t, C_t	1	0.2229641	0.472191	0.3670807	0.605872
		2	0.2040528	0.451722	0.3122488	0.558792
		3	0.1499683	0.387257	0.2601240	0.510024
		4	0.1366765	0.369698	0.2261001	0.475500
		5	0.1210808	0.347967	0.2973856	0.545331
	1,11,12 I_t, C_t	1	0.2950905	0.543222	0.3461342	0.588332
		2	0.1531187	0.391304	0.3603422	0.600285
		3	0.1471724	0.383631	0.4064297	0.637518
		4	0.2202060	0.469261	0.3210728	0.566633
		5	0.1224852	0.349979	0.5476139	0.740009

4. Results of Comparison Study

We concentrate on the dynamic forecasts (data testing) to choose the best model for forecasting inflation in Indonesia. The comparison study uses MSE data testing from the best model in each approach and also ratio of forecast errors of each model to the forecast error of the FFNN model with lags input based on ARIMAX model. The results are presented in Table 4.

Table 4.
Summary of Dynamic Forecasting Performance Comparison

Best Model	MSE (data testing)	Ratio MSE (to FFNN based on ARIMAX)
• ARIMA	0.6826480	3.02
• ARIMAX	0.2407240	1.07
• FFNN with input based on ARIMA	0.4711709	2.08
• FFNN with input based on ARIMAX	0.2261001	1.00

In Table 4, numbers greater than one on the ratio column indicate poorer forecast performance than comparable FFNN with inputs based on ARIMAX model and vice versa. Based on the result at this table, we can conclude that FFNN with inputs based on ARIMAX model, that is input lags 1, 12, I_t, C_t and 4 unit neurons in hidden layer, gives the best dynamic forecast (data testing) for inflation data. The results also show that the forecast accuracy of ARIMAX model is quite similar with the result of FFNN with input based on ARIMAX. This result gives an opportunity for further research by implementing linearity test before applying FFNN to inflation data.

Conclusions

Based on the results at the previous section, we can conclude that the FFNN with inputs such as the Combination Intervention and Calendar Variation Model gives the best result for forecasting inflation in Indonesia. The result also shows that the best FFNN model in training data tends to yield overfitting on testing. This result gives an opportunity to do further research by implementing some NN model selection procedures as explained in Anders and Korn (1999). The results also show that the forecast accuracy of ARIMAX model is similar with the result of FFNN with input based on ARIMAX. Further research about the effect of linearity test in inflation data modeling by using FFNN also can be done.

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